Exploring a Unified Service Data Model for Needs-Based Service Recommendations

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***Abstract*—In recent years, the proliferation of the internet and the impact of COVID-19 have led to an increase in the usage of online services. Consequently, there is a growing demand for service recommendations that are explainable to users. This paper proposes a combination of existing needs extraction techniques and a new service data model to realize an explainable recommendation system. The suggested architecture focuses on matching needs with services. We define a service data model capable of representing a wide range of everyday services and validate its effectiveness through a case study. The proposed system holds the potential to support users in their service selection process in a concise and explanatory manner.**

***Index Terms*—service, recommendation system, explainable AI, need, HCI**

I. Introduction

Decades have passed since the development and proliferation of the internet and digital devices, making it commonplace for many people today to purchase goods and receive services such as video and education through the Web. Furthermore, the COVID-19 pandemic has rapidly transitioned many services, which traditionally involved person-to-person interactions, to web services [1], [2]. However, the vast number of available services makes it challenging for users to select the ones they truly desire. Consequently, research into recommendation systems, which suggest various products to users, has become active [3]. Recent studies have emphasized the importance of explainability in the recommendation process, but adequate explanations for general users are yet to be realized [4]. The aim of this study is to propose a new explainable service recommendation system that elucidates a simple recommendation process through interactive exchanges between the user and the system. The key ideas are twofold. First, leveraging a dialogue-based needs extraction system developed in our previous research, which employs virtual agents [5]. Second, combining this with a newly defined unified service data model that can represent a wide variety of complex services used in everyday life by general users, aiming for needs-service matching. Furthermore, in a case study, we comprehensively consider services and confirm that the proposed model can represent them effectively.

II. Preliminaries

A. Service

The term "service" has diverse interpretations depending on its context. In daily life, it can mean a complimentary item, as in "The first drink is a service." In business, it indicates a sector, such as "This company is in the service industry," or the software in "We developed a Web service." In economics and marketing, its definitions vary widely. Adam Smith saw service as unproductive labor [6]. Colin Clark defined it as non-agricultural, forestry, fisheries, and manufacturing activities [7]. Kotler described it as an intangible benefit without ownership [8]. Looy identified its characteristics as intangibility, simultaneity, perishability, and heterogeneity [9]. Service Science, Management, and Engineering (SSME) views service as an interactive value creation process, and Kameoka considers it as activities supporting goals [10]. No single definition prevails in economics and marketing. In web services, "service" denotes the software itself, as defined by the World Wide Web Consortium (W3C) as systems supporting machine-to-machine interaction [11], [12]. Additionally, Service-Oriented Architecture views "service" as software. This term's meaning also varies across languages and is influenced by cultural perceptions in economics and web services.

B. Explainable Recommendation

Recommendation systems, using technologies like artificial intelligence (AI) and data mining, suggest personalized products based on user preferences across various fields, including e-commerce and e-health [3]. Explainable AI (XAI) makes AI behaviors and rationale comprehensible, addressing the opaqueness of advanced AI methods like deep learning [13]. It varies based on the audience, from AI experts to non-specialists, and involves elements like transparency and fairness. Explainable recommendation research aims to make recommendation systems more transparent and user-friendly, emphasizing AI's explainability and effective Human-Computer Interaction (HCI) techniques [4]. Methods include aligning Matrix Factorization's latent dimensions with explicit features and offering natural language explanations [14].

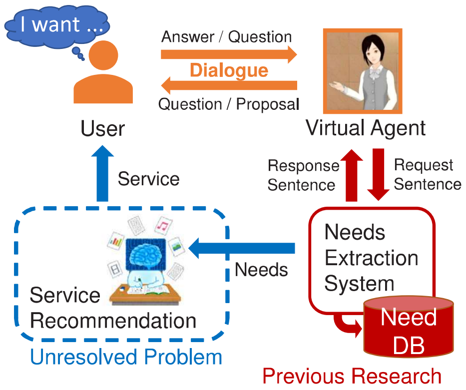

Fig. 1. The architecture of the dialogue-based needs extraction system.

TABLE I
NEEDS DATA MODEL

Element	Description
`how`	What service is to be performed
`why`	The reason or background for performing the service
`what`	Specifically, what is to be done in the service
`when`	When the service is to be performed
`where`	Where the service is to be performed
`who`	Who will primarily perform the service
`whom`	For whom the service is intended

There are two main challenges in explainable recommendation. First, when targeting general users, the AI recommendation process itself is technical and difficult to understand. While there is substantial research on explaining the rationale behind recommendations, the explanations of the recommendation process and its fairness to non-experts are not adequate [4]. The second challenge lies in HCI's limitation to one-way presentation of rationale. It is difficult for users to ask questions or make corrections to machines. A bidirectional approach could potentially enhance understanding of the recommendation process and trust in the system.

C. Previous Research: Needs-based Service Recommendations

In previous research, we proposed an interactive user needs extraction method, shown in Figure 1, aimed at enhancing the explainability of service recommendations [5]. This method uses a voice dialogue agent to gather dialogue content and applies Large Language Models (LLMs) to break down sentences into an understandable, explainable 6W1H (`how`, `why`, `what`, `when`, `where`, `who`, and `whom`) format. The definitions of the 6W1H elements are shown in Table I. Users are asked about any missing 6W1H elements, and they confirm the accuracy of the results at the dialogue's end. This approach aims to increase transparency and user engagement in the recommendation process. However, a challenge is the ambiguity in the explainable recommendation approach and the lack of a service data model that is easily understandable for general users, potentially making service data hard to interpret.

III. PROPOSED METHOD

A. Goal & Key Idea

The objective of this study is to explore the potential of a new explainable recommendation system that enables general users to understand and intervene in the recommendation process, thereby realizing explainable service recommendations. The key idea of the research is to design an outline architecture for the recommendation system using service and needs models from the perspective of explainability. Based on this architecture, the study proposes an easily understandable service data model structured around the 6W1H framework. The specific approach of this research is as follows:

(A1) Designing the scope of the services to be recommended.
(A2) Designing the overview architecture of the recommendation system.
(A3) Defining a unified service data model.

B. (A1) Designing the Scope of the Services to be Recommended

In this research, we address explainable service recommendation, focusing on services utilized by general users in daily life through the Web. The services targeted for recommendation are categorized into two types. The first type includes experiences provided by apps and smart services related to social connections, entertainment, and media. The second type comprises products offered through apps and smart services, such as physical goods and virtual currencies. Several components operate within these services, including user-operable apps, inter-app connectivity mechanisms, physical devices like smart speakers with sensor and microphone input/output capabilities, and external services.

Analyzing the characteristics of the services targeted in this study, it can be said that they may be provided through a wide range of collaborations involving physical goods, works, and people, with Web services at their core, making it challenging to logically define their boundaries. Moreover, the services provide not the software itself but the physical or indirect experiences resulting from various software executions experienced by diverse users. Therefore, it is appropriate to represent the targeted services not by their internal operations but by the user experiences they provide. The concept of experience is easier to explain non-technically and more comprehensible to general users than software explanations.

C. (A2) Designing the Overview Architecture of the Recommendation System

The proposed recommendation system's overview and architecture are illustrated in Figure 2. The system's key feature is to enhance explainability by matching easy-to-understand needs data and service data for general users through explainable AI, thereby presenting results in a user-friendly manner. It operates in the following three steps:

- Step 1. Acquisition of easy-to-understand needs and service data.
- Step 2. Explainable machine learning matching.

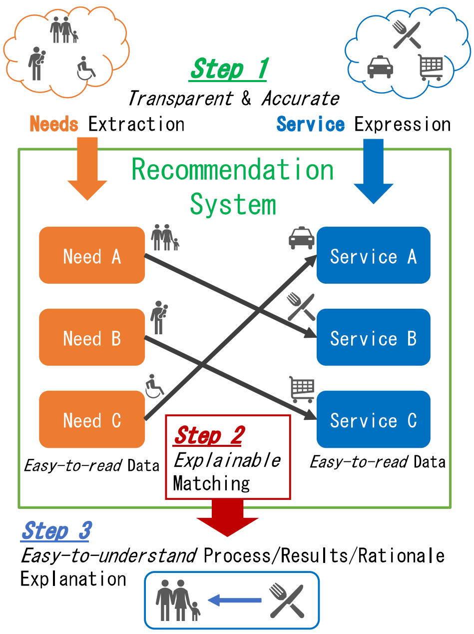

Fig. 2. The architecture of the proposed explainable recommendation system.

- Step 3. Presentation of the process, results, and rationale in a user-friendly manner.

In Step 1, we acquire easily understandable needs and service data. It is essential for both the needs and service data to be easily interpretable and for their generation process to be explainable. Needs data involves sensitive personal information and must be handled with care, while service data should not contain exaggerations or errors. Additionally, the clarity of the data generation process is crucial to maintain the system's overall explainability. While needs data extraction has been addressed in prior research using dialogue-based systems, the development of a comprehensible model and explainable extraction method for service data remains unclear. This study focuses on developing a service data model.

In Step 2, using the service and needs data acquired in Step 1, machine learning matching is conducted in a process explainable to general users. Ideas for machine learning methods include textual similarity between needs and services and recommendations based on service selection history.

Step 3 involves communicating the recommendation results from Step 2 and the rationale for these recommendations in a format understandable to general users. The clarity of the recommendation process explanation depends on the extraction methods in Step 1 and the matching methods in Step 2. An example of explaining the recommendation results and their rationale might be, "Service B is recommended for you because you have need A." Such direct textual or verbal explanations linking specific needs and services become possible due to readability.

D. (A3) Defining a Unified Service Data Model

Based on the analysis results (A1) and architectural design (A2) in this study, the target services for recommendation should express user experience and be modeled in an easily interpretable format suitable for the architecture. The data model is presented in Table II. It consists of eight elements, incorporating the 6W1H structure (`how`, `why`, `what`, `when`, `where`, `who`, `whom`) for ease of understanding, in addition to the `serviceName`. The `serviceName` element succinctly expresses the type of service experience. If an accurate product name exists, it becomes the service name. Each 6W1H element is described in natural language.

TABLE II
PROPOSED SERVICE DATA MODEL

Element Name	Content
`serviceName`	Service name
`how`	Cost, effort, usage method
`why`	Cause, motivation, conditions
`what`	Value, experience
`when`	Time, occasion
`where`	Location
`who`	Affected parties
`whom`	Influenced parties

The `how` element represents the cost and effort users sacrifice for the service, how it is used, and its user interface (UI). The `why` element expresses the reasons or motivations for using the service and its operational conditions. The `what` element describes the value and experience users gain from the service. It also includes visible processes such as CO2 emissions and labor conditions publicized by the service provider. The `when` element details the time or occasion for using the service. The `where` element depicts the physical or logical location of service use. The `who` element represents explicit individuals, institutions, or machines affecting the user through the service. The `whom` element indicates explicit individuals, institutions, or machines, including the user, influenced by the service. A key characteristic of the unified service data model is its exclusion of internal operations and specialized content of the service. It enables the representation of a wide range of services utilized through web services by only expressing user-perceivable experiences.

IV. CASE STUDY

In this study, as a case study of the proposed unified service data model, we comprehensively envisage a hypothetical service example based on the service scope designed in (A1), and verify whether it can be represented using the proposed data model. Specifically, we attempt to represent the following two cases using the proposed data model:

(Case 1) Experiences provided by smart services are depicted in Table III. As it is a smart service, the `how` element describes the operation method via a smart speaker rather than a specific app. The `what` element outlines the experience of music provision. The `how` and `who` elements collectively describe products like smart speakers and related external services like music subscriptions and SNS services.

(Case 2) Products provided through an app are shown in Table IV. As it is a service utilized via an app, the `how` element mentions the app. The `what` element indicates the exchange

TABLE III
(CASE 1) AN EXAMPLE OF EXPERIENCES PROVIDED BY SMART SERVICES

Element Name	Content
`serviceName`	MUSIC DAY (Example Name)
`how`	Requires a music subscription fee. Just say "Play some nice music" to the smart speaker, and it will start playing. If the music isn't to your liking, you can command it to change.
`why`	Useful when choosing music for your room or living area is a hassle.
`what`	Automatically plays music that suits the day's mood and weather.
`when`	Anytime, regardless of the time of day.
`where`	Any place where a smart speaker can be set up.
`who`	Integrates with SNS to play music recommended by friends.
`whom`	The music is audible to everyone around the speaker.

TABLE IV
(CASE 2) AN EXAMPLE OF PRODUCTS PROVIDED THROUGH AN APPLICATION

Element Name	Content
`serviceName`	New Outfit Subscription Service (Example Name)
`how`	Requires a subscription fee. The app requires a personality test and input of clothing preferences.
`why`	For those who want a few new outfits each season. Automatically delivered by mail.
`what`	Sends two sets of new outfits before the change of each season, based on purchase history and test results. Returns are allowed if not liked.
`when`	The basic plan is four times a year, seasonally. A monthly plan is also available.
`where`	Requires a registered delivery address.
`who`	Offers items recommended by favorite brands and influencers.
`whom`	Available only for individual plans.

of tangible products. The entire provision process is described as a service.

V. DISCUSSION

This study contributes to redefining services in the context of economics, marketing, and web services, targeting services in the everyday life of general users in a modern era where web service usage has become almost ubiquitous. The proposed model enables the description of complex services as highly readable data, even for non-experts in service development within service-providing companies, as it does not require consideration of software's internal operations. The proposed system employs a simple recommendation process through the matching of readable needs and service data. Additionally, by combining this with the conversational needs extraction method from previous research, it becomes possible to intervene in the recommendation process through dialogue.

Regarding the limitations of this study, the service data model's reliance on natural language for each 6W1H element may inadvertently lead to the inclusion of incorrect information due to the method of description. Moreover, an explainable method for accumulating service data remains unclear, necessitating a structured definition of each element based on the definitions in (A3). Potential methods for accumulating data include manual input by service providers, users, and automatic generation based on reviews, but how to ensure explainability remains uncertain. Furthermore, the specifics of explainable machine learning for matching and the fairness of data used in machine learning, which impacts the overall fairness of the recommendation system, are unclear.

VI. CONCLUSION

In our study, we designed a unified service data model and system architecture for an explainable service recommendation system tailored to general, non-expert users. This model successfully describes a broad range of daily services, as demonstrated in a case study. The system architecture made the recommendation process simpler, more understandable, and user-intervenable. Future research will explore service data collection methods and matching techniques. Additionally, this research could contribute to building a universal service data repository applicable across industries and research fields.

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REFERENCES

[1] A. Priyono, A. Moin, and V. N. A. O. Putri, "Identifying digital transformation paths in the business model of smes during the covid-19 pandemic," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 6, no. 4, p. 104, 2020.

[2] H.-H. Chang and C. D. Meyerhoefer, "Covid-19 and the demand for online food shopping services: Empirical evidence from taiwan," *American Journal of Agricultural Economics*, vol. 103, no. 2, pp. 448–465, 2021.

[3] Z. Fayyaz, M. Ebrahimian, D. Nawara, A. Ibrahim, and R. Kashef, "Recommendation systems: Algorithms, challenges, metrics, and business opportunities," *Applied Sciences*, vol. 10, no. 21, p. 7748, 2020.

[4] Y. Zhang and X. Chen, "Explainable recommendation: A survey and new perspectives," *Foundations and Trends® in Information Retrieval*, vol. 14, no. 1, pp. 1–101, 2020.

[5] T. Nakata, S. Chen, S. Saiki, and M. Nakamura, "Dialogue-based user needs extraction for effective service personalization," in *HIMI 2023, Held as Part of the 25th HCI International Conference, HCII 2023*, vol. LNCS 14016, July 2023, pp. 139–153.

[6] A. Smith, *An Inquiry into the Nature and Causes of the Wealth of Nations (1776)*. MetaLibri, 2007.

[7] C. Clark, *Conditions of economic progress*. Macmillan, 1957.

[8] G. Armstrong, S. Adam, S. Denize, and P. Kotler, *Principles of marketing*. Pearson, 2014.

[9] B. V. Looy, R. van Dierdonck, and P. Gemmel, *Services management: An integrated approach*. Pearson Education Limited, 2003.

[10] A. Kameoka, *Service Science - Toward Innovation Management for a New Era*, J. A. I. o. S. Editorial Board of MOT Course, Technology, and S. S. I. LLP, Eds. N-T-S, 2007.

[11] T. Aoki, *Web Service Computing*. IEICE, 2005.

[12] W. W. S. C. W. Group, "Web services glossary," http://www.w3.org/TR/2004/NOTE-ws-gloss-20040211/, February 2004, (Accessed on 12/19/2023).

[13] D. Gunning and D. Aha, "Darpa's explainable artificial intelligence (xai) program," *AI magazine*, vol. 40, no. 2, pp. 44–58, 2019.

[14] S. Rendle, W. Krichene, L. Zhang, and J. Anderson, "Neural collaborative filtering vs. matrix factorization revisited," in *Proceedings of the 14th ACM Conference on Recommender Systems*, ser. RecSys '20. New York, NY, USA: Association for Computing Machinery, 2020, pp. 240–248.